A fuzzy logic apparel size decision methodology for online marketing

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Abstract

Purpose – Beside the development of technology and accessibility, ease of use, ability to reach various products and compare many products at the same time make online shopping even more popular. Despite the great advantages provided by online shopping for either consumers or retailers, there are certain issues that must be solved to improve online shopping advantages. Finding right size is one of the biggest barriers against apparel online retailing. Since the use of apparels is directly related with fitting, choosing right size is becoming more critical for retailers and consumers. The purpose of this paper is to contribute to the solution of the problem.
Design/methodology/approach – For the study, the specific size measurements of male shirts (collar, shoulder, chest, waist, arm length in cm) from four different sizes (small, medium, large, x-large) and from eight different brands were collected and stored in a database. Totally, weight, height and body measurements (collar, shoulder, chest, waist and arm length in cm) of 80 male candidates, between the ages of 18 and 35, were measured individually. These data were then used for experiments.
Findings – Any product with known measurements can be compared with users' body measurement based on fuzzy logic rule and the best-fitted size can be selected for users. Similarly, using the proposed web design, users are able to see desired products on users with similar body type.
Originality/value – In this study, a new mathematical method based on fuzzy relations for apparel size finder is proposed. Beside, this method can group users based on body measurements in order to find people with similar size.

Keywords Online marketing, Fuzzy modelling, Fitting, Apparel size

Paper type Research paper

1. Introduction

Online retailing has increased after the invention of the internet and is still increasing to expand market share. With the advent of the internet and the subsequent introduction of digital technologies, retailers have increasingly utilized online platforms to sell goods and services. At the same time, the widespread availability of internet connectivity and the smartphone revolution have turned consumers into virtual citizens who increasingly do their shopping online. An investigation between online shoppers to find out what are the main reasons for buying the online shows that the convenience of internet shopping and cheaper than traditional

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shopping style are two main reasons in all countries behind online shopping (PWC, 2016). The market share of online marketing has been increasing year by year in all categories as well as online apparel sales. In the UK, non-food online sales moved from 11.6 percent in the total market to 24.1 percent between 2012 and 2017 (Bowsher, 2018). Just in the US apparel and accessories, online sales amounted to US$72.13bn and are projected to increase to $116.3bn in 2021 (www.statista.com). In Turkey, online marketing expanded market share approximately 11 percent between 2016 and 2017 and 62.3 percent of all online sold products were apparel and sportswear (KPMG, 2018). All research and statistics show that online marketing is an irreversible piece of our lives and will become more effective by growth in the future.

Even though the entry barriers of the e-retailer environment are really low and it seems sufficient that a low price is enough to start the e-business, in such an environment, where alternative suppliers are a few clicks away, the key of success is much more than simple and cheap service. Creating customer value and making loyal customer are the basic elements for growth and survive (Zeithaml, 1998; Zeithaml *et al.*, 2001). Additionally, despite the dramatic increase in the number of visitors who come to a retailer website, only a small amount of those visitors actually make a purchase in online marketing (Lee and Overby, 2004). Woodruff (1997) proffered that online shoppers choose retailers who offer the best value for them – value defined by consumers. Offering customer value and making them loyal are one of the major drivers of success. When consumers are loyal, they minimize searching and evaluating alternatives. One of the objectives of this study is to create value for customers to make them loyal for e-retailer.

For the reason of sensory and interactive nature of the apparel buying process, apparels are categorized under high-risk items (Bhatnagar *et al.*, 2000). Before purchase decision, the consumer wants to examine the product to evaluate color, fabric, touché and design (Ha and Stoel, 2004). In apparel online retailing, creating factors that consumer relates as value and consumer satisfaction has strict relation with physical experience (Song and Ashdown, 2010). Cordier *et al.* (2001) showed that the lack of physical experience is a basic reason why consumers hesitate to buy online. Since the use of the purchased product depends on the choice of the right size, fitting is even more important than all other physical properties. "Choosing right size" is cited as one of the biggest barriers against apparel online retailing (Merriam, 2009; Pastore, 2000). Beck proposed that choosing inappropriate apparel size is the main factor that why consumers do not buy apparel online. Any products are not counted good quality if they do not fit users (Kim *et al.*, 2007). Misra and Arivazhagan (2017) stated that 42 percent of returned apparels in online marketing was because of poor fit and size selection.

Choosing inappropriate apparel size causes consumer dissatisfaction as well as extra costs for suppliers and consumers. When consumers are not happy with the size of online purchased apparel, they return it. This return means extra time for consumers to reach desired products and it eliminates one of the main advantages of online purchasing. Besides extra costs such as customer service costs, cargo and labor costs, resale of the product and loss of customer loyalty, the decrease in profit margin also shows up for online retailers. To eliminate the lack of physical experience, consumers started to use online and offline shopping channels together. In total, 44 percent of consumers search online and buy online, while 51 percent of consumers search online and buy offline. Besides, 32 percent of consumers search online, experience offline and buy online, while only 17 percent of consumers search and buy online (TUSIAD, 2017). Mixing online and offline channels together decreases the effectiveness of online marketing and can be count an obstacle to expand market share for certain products.

In many studies, researchers focused on to eliminate the drawbacks of the lack of physical experience in apparel online retailing. Due to the fact that online shoppers have to rely on the picture and characteristics of products that are provided by the seller, Fiore and Jin (2003) proposed that more purchases could be made by increasing information transferred to the user through the visualization of the products on the internet. For this purpose, many researchers and firms have studied on fitting computer-based created apparels on computer-based 3D avatars such as "Human solutions," "Mport," "Styku" and "Size stream" (Petrak and Rogale, 2006; Judy, 2017). For creating 3D avatars, above-mentioned applications and researchers use different techniques. Mport uses body measurements such as height, weight, biceps, chest, knees, waist/hip ratio, waist/height ratio, etc. "Styku" and "Size stream" use body scanner to create avatars. Wuhrer and Shu (2012) used 1D measurements to create 3D avatars. Apeagyei (2010) also used 3D body scanning technology for human measurement for clothing size. However, Merle *et al.* (2012) claimed that creating the 3D avatar and virtual fitting on it do not have a great influence on consumer purchase decision. Besides, many firms use limited dimensions in size tables to select the size and it makes even more difficult to decide true size on 3D avatars. Randall (2015) also stated that virtual fitting room is not an effective solution yet.

Apparel recommendations systems were also developed based on different purposes and principles. Guan *et al.* (2016) classified apparel recommendation systems into four main categories as clothes searching/retrieval systems, wardrobe usage history systems, fashion coordination, and intelligent recommendations systems. Recently, many mobile phone applications and websites that work on different principle have been also developed to help to find the right apparel size for users. These applications and website use body shape, weight, height, bra size, body measurements and similar data that give some clue about user size (Consumer Reports, 2014). Despite many attempts to solve fitting solutions with a different perspective, there are no exact solutions for the whole industry (Buckner, 2017). Using the size of previously bought apparels to predict the size of future desired apparels is not always a perfect solution. Despite many brands use the same size representations such as S-M-L-XL, etc. – these size standards may vary between brands. Besides, various fit options (slim-, regular-, modern-fit) for the same brand could also mislead consumers for choosing the right size. All these tricky processes inspire us to design a system that helps online buyers to choose the best-fitted size without the effect of existing brand classification.

In this study, previously proposed fuzzy logic based apparel size finder method (Demir *et al.*, 2017) was applied to search the most appropriate apparel size for the users' measurements. Moreover, a methodology to determine the most similar products purchased by most similar users is proposed using similarity and distance metrics. For the application, shirts' data for men of specific brands and body measurements of 80 males between the age of 18 and 35 were collected. A sample web application was developed to display the best-fitted size amongst all given brands for users, and classify similar users based on body measurements.

2. Method

In this study, it was aimed to detect the best-fitted size of particular brands' products for a user with known body measurements via the fuzzy logic approach.

For the study, male shirts were selected as an example of application to make easier to collect data from candidates. For an example of the male shirt, fitting problems were reported for specific sizes such as tail length, sleeve length, neck circumstance, cuffs circumstance, waist circumstance, and collar width. Therefore, specific size measurements of shirts that are directly related to the fitting perception of consumers (collar, shoulder, chest, waist and arm length in cm) from four different sizes (small, medium, large and x-large) were collected and stored in a database. Male shirts from eight different popular brands were chosen for the study. The production measurements were obtained for each size of the shirts. As for the users, weight, height and body measurements (collar, shoulder, chest, waist, arm length in cm (the metric system used in Turkey)) of 80 male Turkish university students and researcher candidates, between the age of 18 and 35, were measured individually.

2.1 *Determining the most appropriate size of the apparel*

The system is designed to calculate the fitness degrees (or class membership values) of n users (customers) $C = \{c_1, c_2, \ldots, c_n\}$, according to m different sizes (e.g. "small," "medium," "large," etc.) of products $P = \{p_1, p_2, \ldots, p_m\}$ for a selected brand. Each product is defined with k attributes (e.g. "collar," "shoulder," "chest," "waist," etc.). Similarly, each user has its size measurement value for each kth attribute. The measured values of all k attributes for all n customers can be given via the relation R^1: $C \times A \rightarrow (-\infty, +\infty)$ which can be defined as follows:

$$R^1 = \begin{bmatrix} r^1_{11}, & r^1_{12}, \ldots, & r^1_{1k} \\ r^1_{21}, & r^1_{22}, \ldots, & r^1_{2k} \\ \ldots & \ldots & \ldots \\ r^1_{n1}, & r^1_{n2}, \ldots, & r^1_{nk} \end{bmatrix}, \tag{2.1}$$

where $r^1_{ij} \in (-\infty, +\infty)$ is the numerical value of jth size measurement (attribute) of ith user. The fuzzy numbers corresponding to the related attribute of a particular product are constructed with the relation R^2: $A \times P \rightarrow [0, 1]$:

$$R^2 = \begin{bmatrix} r^2_{11}, & r^2_{12}, \ldots, & r^2_{1p} \\ r^2_{21}, & r^2_{22}, \ldots, & r^2_{2p} \\ \ldots & \ldots & \ldots \\ r^2_{k1}, & r^2_{k2}, \ldots, & r^2_{kp} \end{bmatrix}, \tag{2.2}$$

where r^2_{ij} in R^2 represents the fuzzy number which reflects the ith attribute of the jth product. Each fuzzy limitation for each attribute value of the product is represented via μ_{ij} triangular fuzzy number (Figure 1). Let us remember that the fuzzy number $T(a, b, c)$ is calculated by triangular membership function as:

$$\mu_T(x) = \begin{cases} 0, & x < a \text{ or } x > c \\ (x-a)/(b-a), & a < x \leqslant b \\ (c-x)/(c-b) & b < x \leqslant c \end{cases}. \tag{2.3}$$

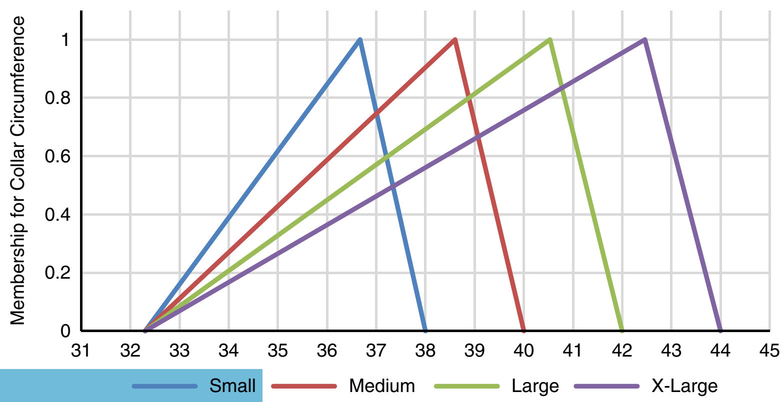

Figure 1.
Size membership functions for collar circumference of brand X

The fitness value of relationships between the size measurements of the customers and the particular product can be obtained using "min-min" composition in $R^3 = R^1 \circ R^2$:

$$R^3 = \begin{bmatrix} r^3_{11}, & r^3_{12}, \ldots, & r^3_{1p} \\ r^3_{21}, & r^3_{22}, \ldots, & r^3_{2p} \\ \cdots & \cdots & \cdots \\ r^3_{n1}, & r^3_{n2}, \ldots, & r^3_{np} \end{bmatrix}. \tag{2.4}$$

The r^3_{ij} value in relation R^3, representing the fitness degree of ith user to jth product according to all measurements, is computed as:

$$r^3_{ij} = \min_{l=1,\ldots,k} \mu_{lj}\left(r^1_{il}\right), \tag{2.5}$$

where $\mu_{lj}\left(r^1_{il}\right)$ is the degree of fitting of the ith user's lth size measurement $\left(r^1_{il}\right)$ to the lth fuzzy attribute limitation of the jth product.

2.2 Detecting the most similar user and product images

Assume that a client C wants to buy a product X. The system queries the database to retrieve the most similar products to X and buyers of these products. This query depends on the following relations:

- the similarity relation R^4 defining the most similar products to product X;
- the similarity relation R^5 defining the most similar clients to the client C; and
- the relation R^6 between the clients and the products they bought.

It is obvious that R^4: $P \times P \rightarrow [0, 1]$ is the relation that explains the fuzzy relation of similarity between the products. The similarity is calculated upon the closeness or proximity of the attributes using Euclidean distance measure. The distance between products $p_1 = (p_{11}, p_{12}, \ldots, p_{1k})$ and $p_2 = (p_{21}, p_{22}, \ldots, p_{2k})$ with k attributes is:

$$D^1(p_1, p_2) = \sqrt{(p_{11}-p_{21})^2+(p_{12}-p_{22})^2+\ldots+(p_{1k}-p_{2k})^2}. \tag{2.6}$$

In order to normalize the distance measures in the interval [0, 1], $D^1(p_1, p_2)$ is divided by the maximum distance value:

$$D^1(p_1, p_2) = \frac{D^1(p_1, p_2)}{D^1_{max}} \in [0, 1], \tag{2.7}$$

where $D^1_{\max}$ is the maximum distance among all products. The similarity measure between p_1 and p_2 is obtained by:

$$R^4(p_1, p_2) = 1 - D^1(p_1, p_2). \tag{2.8}$$

Applying the same steps within the clients, the difference between clients c_1 and c_2:

$$D^2(c_1, c_2) = \sqrt{(c_{11}-c_{21})^2+(c_{12}-c_{22})^2+\ldots+(c_{1k}-c_{2k})^2} \tag{2.9}$$

is again normalized to [0, 1] interval by:

$$D^2(c_1, c_2) = \frac{D^2(c_1, c_2)}{D^2_{\max}} \in [0, 1]. \tag{2.10}$$

Here, D^2_{max} is the maximum distance among all clients, and the similarity measure between clients c_1 and c_2 is obtained by:

$$R^5(c_1, c_2) = 1 - D^2(c_1, c_2). \tag{2.11}$$

The relation R^6: $C \times P \rightarrow \{0 \vee 1\}$ is defined as:

$$R^6(c_i, p_j) = \begin{cases} 1, & \text{client } c_i \text{ has bought product } p_j, \\ 0, & \text{otherwise.} \end{cases} \quad i = 1, \ldots, n; j = 1, \ldots, m. \tag{2.12}$$

As a result, the relation R^7 which defines the most similar images of the products that the client wants to buy is computed as a composition of R^4 (similarity between the products), R^5 (similarity between the clients) and R^6 (clients and products they bought) by using the fuzzy relation in:

$$R^7 = R^5 \circ R^6 \circ R^4 \tag{2.13}$$

Representing R^7 in matrix products:

$$R^7 = R^5 \times R^6 \times R^4, \tag{2.14}$$

where the product is "min-max" compositions in matrices.

An algorithm that lists the similar images to a specific product of a client willing to buy can be represented as follows:

(1) The client ID (c^*) and product ID (p^*) that the user thinks to buy are entered.

(2) Fuzzy set of similar clients to c_* is constructed by:

$$R^5(c_*, c_i) = 1 - D^2(c_*, c_i). \tag{2.15}$$

where:

$$D^2(c_*, c_i) = \frac{\sqrt{(c_{*1} - c_{i1})^2 + (c_{*2} - c_{i2})^2 + \ldots + (c_{*k} - c_{ik})^2}}{D^2_{max}}, \tag{2.16}$$

and D^2_{max} is the maximum value of distance measured between the clients.

(3) The fuzzy set of similar clients to c_* is represented as:

$$BC(c_*) = \{(\mu_{c_*}(c), c) | c \in C\}, \tag{2.17}$$

where $\mu_{c_*}(c) = R^5(c_*, c)$ is the fuzzy similarity measure of client c_* to client $c \in C$.

(4) The set of products (denoted as $BP(c_*)$) similar to the product which client c_* thinks to buy is constructed using the relation R^6 (client – product relation) matrix:

$$BP(c_*) = \cup_{i=1}^{n} \cup_{j=1}^{P} \left(\mu_{c_*}(c_i) \Lambda R^6(c_i, p_j)\right). \tag{2.18}$$

(5) Among these products, the set of similar ones to p_* for client c_* is selected:

$$BSP(c_*, p_*) = BP(c_*) \Lambda \cup_{j=1}^{P} R^4(p_*, p_j)$$

$$= BSP(c_*, p_*) = \cup_{i=1}^{n} \cup_{j=1}^{P} \left(\mu_{c_*}(c_i) \Lambda R^6(c_i, p_j) \Lambda R^4(p_*, p_j)\right). \tag{2.19}$$

(6) Considering the client similarity and product similarity between c_* and p_*, the membership degree any product p to this duo can be expressed as:

$$\mu_{(c_*,p_*)}(p) = V_{i=1}^{n} V_{j=1}^{P}\left(R^5(c_*, c_i)\Lambda R^6\left(c_i, p_j\right)\Lambda R^4\left(p_*, p_j\right)\right). \tag{2.20}$$

(7) The products p_i, $i = 1, \ldots, P$, in the last set are sorted in descending order by the membership values:

$$\mu_{(c_*,p_*)}(p_1) \geqslant \mu_{(c_*,p_*)}(p_2) \geqslant \ldots \geqslant \mu_{(c_*,p_*)}(p_P). \tag{2.21}$$

(8) The images of the particular number of products at the top of the sorted list of products are displayed to the client to give an idea about how the product will look on him/her visually. If any product in the list has no visual images recorded to the database, the next product is considered to display the image to the user.

3. Computational example

3.1 Detecting the most appropriate size

Detecting the most appropriate size of a user was showed by Demir *et al.* (2017), and it is also given under this section. Each size of a brand is considered as a separate product, and all separate products are numbered as 1, 2, …, p. As an example, a specific X brand of shirts is supposed to have different sizes such as "Small," "Medium," "Large" and "XLarge." The measurements for these size of brand X are given in Table I.

The following rules are considered for constructing suitable fuzzy intervals:

- Measurements smaller than client's attribute value are considered to be inappropriate for the client's body size.
- Most suitable size value for the client is determined by the value of 96.5 percent of the upper value of the related size according to the best-fitting value for textile standards.
- Sizes with larger measurements than a client also have some fitness degree. A client in "Small" size has also a small membership value for "Large" size. But a "Large" sized user has 0 membership value for size "Small."

The fuzzy numbers constructed for sizes "Small," "Medium," "Large" and "XLarge" are in form of triangular fuzzy numbers defined as $T(a, b, c)$, where T denotes one of the sizes of "Small," "Medium," "Large" or "XLarge," a is the lower limit of the all sizes, b is the optimum measurement for the handled size and c is the upper limit of the related size. Figure 1 is an example of membership function used for the attribute "collar circumference" for all sizes in a brand. Functions for shoulder, chest and waist have the similar shape but different lower and upper limit and core point values.

As an example, suppose that a client C has measurements as C (collar = 38 cm, shoulder = 44 cm, chest = 104 cm and waist = 94 cm). By default, the lower limit of all sizes is calculated as 85 percent of the upper limit for convenience (38 cm for "Small" size in this example). This lower limit value corresponds to value a of $T(a, b, c)$. The most fitting value of

	Small (cm)	Medium (cm)	Large (cm)	XLarge (cm)
Collar	35–38	39–40	41–42	43–44
Shoulder	38–42	43–44	45–46	47–48
Chest	90–98	99–104	105–110	111–114
Waist	40–46	47–52	53–54	55–56

Table I. Size measurements for brand X the size is 96.5 percent of upper value of the related size (3.5 percent less than the upper limit). For example, *a*, *b*, *c* parameters for "Small" size of "Collar" measurement in brand X are *T*(32.3, 36.67, 38). The parameter table for "Collar" in "Small" size is shown in Table II.

The client C with 38 cm collar circumference measurement has a membership value $\mu_{(\text{Small, Collar})}(38) = 0$ for "Small" size, and $\mu_{(\text{Medium, Collar})}(38) = 0.905$ for "Medium" size for brand X.

After calculating the membership values for all attributes in all sizes, the membership degrees for sizes of client C are obtained. For example, the degree of fitness for this client C to size class "Small" is computed as:

$$\mu_{\text{C,Small}} = \mu_{(\text{Small,Collar})}(38) \wedge \mu_{(\text{Small,Shoulder})}(44) \wedge \mu_{(\text{Small,Chest})}(104) \wedge \wedge \mu_{(\text{Small,Waist})}(94). \tag{3.1}$$

After computing class membership values for each size (i.e. "Small," "Medium," "Large," "XLarge") for client C, the product size with the highest membership value is assigned as the most suitable size for the client. In other words, the size that provides:

$$\max(\mu_{\text{C,Small}}, \mu_{\text{C,Medium}}, \mu_{\text{C,Large}}, \mu_{\text{C,XLarge}}), \tag{3.2}$$

is the best-fitting size for the users within the given parameters. Table III represents the fitness values and classification for particular client C.

3.2 Finding the most similar users and product visuals

When a user logs in the system and clicks on "Most Similar Users" button, the Euclidean distances are calculated between the current user and the other users in the database. During this process, the measurement values are transformed to [0, 1] interval using "min-max normalization" to defeat the incompatibility in ranges. In accordance with data mining techniques (Han and Kamber, 2001; Larose, 2005), the min-max normalization of a value x is computed in the data preparation phase as follows:

$$x_{\text{new}} = \frac{x_i - \min(x)}{\max(x) - \min(x)}. \tag{3.3}$$

The real and normalized measurement values of the users are simply viewed in Table IV.

Table II. Parameters for "small" size in "collar" attribute

Size (collar)	a	b	c
Small	32.3	36.67	38
Medium	32.3	38.6	40
Large	32.3	40.53	42
X-Large	32.3	42.46	44

Table III. Membership values for a user to size classes

Measurement	Small	Medium	Large	X-Large
Collar (38 cm)	0.00	0.42	0.32	0.26
Shoulder (44 cm)	0.00	0.00	0.55	0.45
Chest (104 cm)	0.00	0.00	0.55	0.45
Waist (94 cm)	0.00	0.39	0.33	0.29
Member to	0.00	0.00	0.32	0.26

In the application, the distances between the current user and the other users are calculated and the similarity measure is constructed by subtracting this difference from 1, i.e.:

$$S(x,y) = 1 - d(x,y), \tag{3.4}$$

where:

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}, \tag{3.5}$$

is the normalized Euclidean distances between the registered users x and y. It is clear that as the distance increases, similarity measure decreases. The difference between the two instances with the same attribute values is 0, but the similarity measure is 1. If two instances are very similar, then the distance between them will be near to 0, but the similarity measure will be close to 1.

In this case, the similarity of any instance to itself will be 1. As the similarity increases, the similarity measure will be close to 0. Table V shows the similarity measures of a selected user C1 (M**** D****) to the others.

Similarity measure between M*** D*** (C1) and F*** S*** (C2) is calculated as follows:

$$\begin{aligned} S(\mathrm{C1},\mathrm{C2}) &= 1 - d(\mathrm{C1},\mathrm{C2}) \\ &= 1 - \sqrt{(\mathrm{C1}_{\mathrm{Chest}} - \mathrm{C2}_{\mathrm{Chest}})^2 + (\mathrm{C1} - \mathrm{C2}_{\mathrm{Collar}})^2 + \ldots + (\mathrm{C1}_{\mathrm{Waist}} - \mathrm{C2}_{\mathrm{Waist}})^2} \\ &= 1 - \sqrt{(0.4857 - 0.4286)^2 + (0.5111 - 0.5556)^2 + \ldots + (0.5714 - 0.5714)^2} \\ &= 0.8411 \end{aligned}$$

So, similarity degree between M*** D*** (C1) and F*** S*** (C2) is: $S(C1, C2) = 0.8411$.

Besides the similarity of users, the system also compares the similarities between the selected product and the most similar other products which have been bought by the most similar users. Table VI shows the similar products bought by other users to the product that client C1 is interested in.

Finally, the degrees of the most similar products and the most similar customers are given in descending order in Table VII.

User	Chest	Collar	Shoulder	Waist
M**** D****	104 (0.4857)	38 (0.5111)	44 (0.0889)	94 (0.3867)
F****** S****	100 (0.4286)	40 (0.5556)	45 (0.1111)	94 (0.3867)
İ***** İ****	100 (0.4286)	40 (0.5556)	43 (0.0667)	93 (0.3733)
K***** S**	96 (0.3714)	41 (0.5778)	48 (0.1778)	91 (0.3467)
H**** S***	96 (0.3714)	40 (0.5556)	44 (0.0889)	91 (0.3467)

Table IV.
Real measurements and min-max transformed (in brackets) values for users

User	Similarity degree of the user
M**** D**** (C1)	1.0000
F****** S**** (C2)	0.8411
İ***** İ**** (C3)	0.7098
K***** S** (C4)	0.7585
H**** S*** (C5)	0.7900

Table V.
Similar users and their similarity degree to the registered user C1

4. A sample web interface

A web application is designed using the theoretical and methodological approaches developed in the study. The application is designed in Windows, in programming language ASP.Net and C#. The tools and versions are as follows:

- Visual Studio 2015 Express.
- ASP.Net 4.x.
- ASP.Net Web Form.
- C# 6.0.
- IIS Express 10.
- Bootstrap v3.0.
- Flatly Theme (bootswatch.com).

4.1 User and brand information

The users are asked to enter some physical information (e.g. age, height, weight) and the body size measurements (collar, shoulder, chest, waist, arm length in cm) to be used in the system. The web interface explains how each attribute should be measured in detail using sample pictures (Figure 2). When the users click on the related measure to enter, a figure explaining how to measure is displayed on the screen. The system also needs the specific size measurement of the products for the related brands. The "Brand" class design was implemented simply for effectiveness. The Brand class may contain some sub-classes because even a single brand may contain different sizes for specific products. Some brands have not provided some of the measurements like abdominal circumference or product height but the algorithm can use the present data to compare the product and the user sizes. Table VIII represents the sizes for Brand "A" products.

Table VI.
Similar products and user measurements for the product that *C*1 is interested in

Product – Size	Chest	Collar	Shoulder	Waist	Similarity of the product	Bought by the user
Brand01 – Slim Fit Large	110 (0.5714)	42 (0.6000)	46 (0.1333)	108 (0.5733)	1.0000	C1
Brand02 – Regular Fit Medium	120 (0.7143)	42 (0.6000)	50 (0.2222)	98 (0.4400)	0.7778	C2
Brand03 – Slim Fit X-Large	120 (0.7143)	44 (0.6444)	42 (0.0444)	98 (0.4400)	0.7734	C2
Brand04 – Regular Fit Large	100 (0.4286)	38 (0.5111)	52 (0.2667)	107 (0.5600)	0.7685	C3
Brand05 – Slim Fit X-Large	105 (0.5000)	41 (0.5778)	42 (0.0444)	111 (0.6133)	0.7653	C4
Brand06 – Slim Fit X-Large	114 (0.6286)	48 (0.7333)	54 (0.3111)	108 (0.5733)	0.7551	C5
Brand07 – Regular Fit Large	111 (0.5857)	37 (0.4889)	51 (0.2444)	122 (0.7600)	0.7539	C5

Table VII.
Similar products bought by similar users for the product that *C*1 is interested in

Product – Size	Similarity of the product	Bought by the user	Similarity of the user	The overall degree
Brand01 – Slim Fit Large	1.0000	C1	1.0000	1.0000
Brand02 – Regular Fit Medium	0.7778	C2	0.8411	0.7778
Brand03 – Slim Fit X-Large	0.7734	C2	0.8411	0.7734
Brand04 – Slim Fit X-Large	0.7653	C4	0.7585	0.7585
Brand06 – Slim Fit X-Large	0.7551	C5	0.7900	0.7551
Brand07 – Regular Fit Large	0.7539	C5	0.7900	0.7539
Brand08 – Regular Fit Large	0.7685	C3	0.7098	0.7098

There are 8 different size subgroups for brand "A" under the sizes "Slim Fit" and "Regular Fit" named as "Small," "Medium," "Large" and "XLarge."

The "Size" class for the products stores a range as an interval instead of integer values. The aim is to express the constant measurements of sizes in terms of fuzzy numbers. As an example, it is obvious that a product of brand "A" in "Slim Fit – Small" which has 38 cm collar circumference is not suitable for a user with collar size 40 cm. In this case, the maximum value of range type will be 38 cm, so that the fuzzy number will correspond to 0 for measurements over 38 cm for Slim Fit – Small size. As the users with smaller collar size can wear the product, it must be considered that lowering the user's size will widen the product for the user. This will cause a decrease in the preferment of the product. To avoid this, the minimum value is considered as 85 percent of the maximum size measurement value for all the sizes.

4.2 Constructing fuzzy limitation for sizes

To represent a size in terms of fuzzy numbers (limitation), triangular fuzzy numbers in form $\bar{A}(a, b, c)$ are used. Using $\bar{A}(a, b, c)$, the $c = X$; $a = X * 0.85$ and $b = X * 0.0915$ values are calculated for a specific size "X." $\mu_{\bar{A}}(x)$ is the membership value of a user's measurement "x" for the size "X" of a product.

The fuzzy representation for collar size of a product in brand "A" is displayed in Table IX. The left boundary of triangular region of fuzzy numbers is considered to be the smallest measurement in all sizes.

This approach guarantees a user in "Small" size to be considered in "Medium" size also but with a low membership value. To list the membership values in descending order for a user to sizes, the most appropriate size for him/her will be listed at the top of the list. The membership values can be observed in Figure 1 in the previous section. A user with 35 cm collar circumference has a membership value for all size classes. This value is highest in "Small" and lowest in "XLarge." But a user with 39 cm collar size is definitely not a member to "Small" class but member to other size classes.

Figure 2. The explanation for the measuring

	Slim Fit					Regular Fit				
Size	Collar	Shoulder	Chest	Arm	Waist	Collar	Shoulder	Chest	Arm	Waist
Small	38	42	49	62.5	46	40	44	54	62	52
Medium	40	44	52	65	52	40	46	57	64	54
Large	42	46	55	65	54	42	48	60	66	58
X Large	44	48	57	67	56	44	50	65	68	63

Table VIII. Size table for brand "A"

Brand A slim fit	Measurement in cm		
Collar		Min (X * 0.85)	X * 0.0915
Small	38	32	37
Medium	40	32	39
Large	42	32	41
XLarge	44	32	43

Table IX. Collar size representation for "Slim Fit" products in brand "A"

4.3 Searching the most appropriate product for the user's size

The application is designed for the users to find the necessary information he/she is searching for. The user can view the specific or all brands by clicking the "Search" button. The user is reported with a list of membership values calculated using the user's measurements for all sizes of the selected brands in descending order. If "Hide Bad Memberships" option is selected, the sizes with 0 membership value are removed from the list (Figure 3).

Clicking on any row of the search result list displays the measurement table in detail for the clicked brand and size. Table X shows the screenshot of the detailed list displayed under the clicked product.

When the mouse is over on a specific row of the detailed list, the graphical representation of the membership value of the user to the selected size is displayed. The user can see the corresponding fuzzy membership value of his/her real measurement for the specific size.

Table X contains columns of percent, difference, membership and size, as described below:

- Size: measurements of the user to be used in the related row like collar, chest, shoulder, etc.
- Membership: the membership value of the user's measurement to the selected size. Represented as $\mu_{\overline{A}}$(Measurements).
- Difference: the difference between the user's measurement and the selected size of the brand. This value is not a fuzzy number and calculated using the size measurement of the selected product.
- Percent: calculated as (Difference/Measurement of the size)×100.

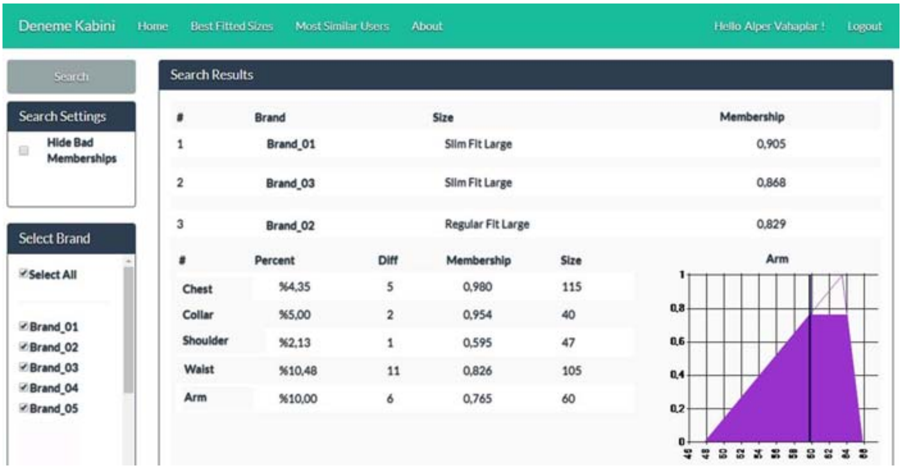

Figure 3.
Detailed list for the user's search results

Table X.
Contents of details

Measurement	Percent	Diff.	Membership	Size
Chest	4.35	5	0.980	115
Collar	5.00	2	0.954	40
Shoulder	2.13	1	0.595	47
Waist	10.48	11	0.826	105
Arm	10.00	6	0.765	60

The example in Figure 4 is the graph of fuzzy number representation for “Arm” in “Regular Fit – X Large” size of brand “A.” It is seen that the fuzzy number representation is (48, 65, 68). The vertical line is the “Arm” measurement of the user. Area under the intersection of user’s measurement and fuzzy graph is shaded to emphasize the membership.

4.4 Similar users and product visuals menu

The website constructs a list of users which have purchased the related and/or similar product to the desired product of similar measurements with the current user in accordance with similarity values.

The search results for similar users can be filtered by the threshold value and the product. The similarity values between users are placed in [0, 1] interval. The value of 1 means that displayed user has the value of the same measurements with the current user. As this value increases, similarity increases too. Threshold value filters even the least similar users having a similarity value below the adjusted threshold and the least similar product with the product that current user is interested in. If adjusted as 0.7, the users and the products with lower similarity value than 0.7 will be filtered. Selecting “All” from the product section will display all the products purchased by the similar users.

The search page can be retrieved by the link “Most Similar Users” in the menu on the top of the page simply. The page is displayed with the default value of 0.7 and all products results are seen in Figure 5.

In the example displayed in Figure 5, a user named E*** K*** is the most similar user to the currently logged in user with a similarity measure of 0.88. Below the user, the products that he/she purchased are listed. The similarity degrees are all 1 in the figure because of the selection “All” in product filter. Figure 6 displays a filtered result with threshold = 0.8 and product = “Brand02 @ Slim Fit Medium.”

Clicking on any of the products listed in the search results page opens a pop-up window displaying images of the similar user with the product purchased. By this way, the logged user can have an opinion about the product which he/she is interested in seeing it worn by a user with similar measurements to himself/herself (Figure 7).

To estimate the overall accuracy for the system, randomly chosen 20 of the participants tried the shirts for all sizes of all brands and asked for which he felt most comfortable/most suitable for himself (Figure 8). In total, 18 of the participants’ responses matched with the system’s proposal which gave the higher similarity measure for that particular user. Two of the users preferred the next larger size that the system offered. So, for a test of 20 samples, the system has true classification rate of 18/20 = 0.90. Generally, the system is said to have 90 percent accuracy in classifying the user with the true size of a product.

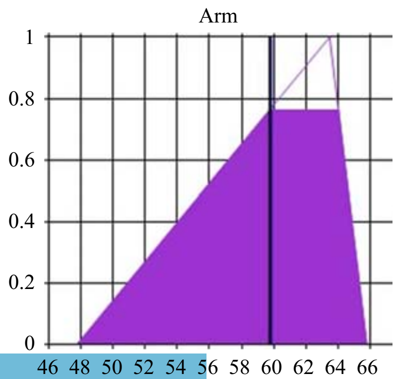

Figure 4.
Fuzzy number graph for “Arm” of the related user

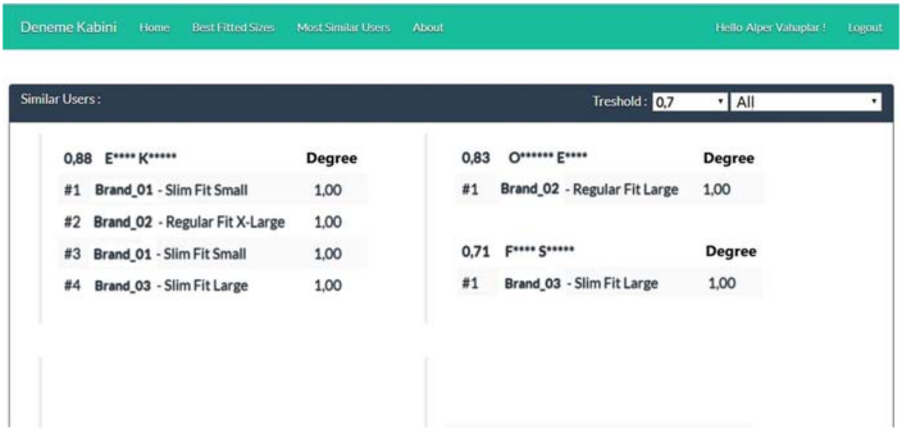

Figure 5.
Search results for "most similar users"

Figure 6.
Results with threshold = 0.8, and product = Brand_02 @ Slim Fit Medium

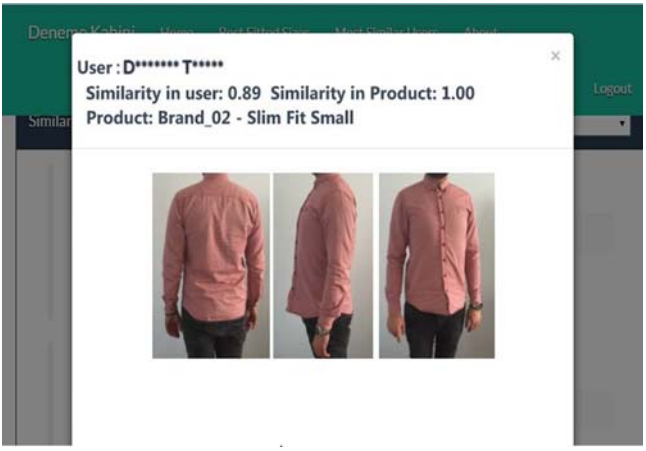

Figure 7.
Visual of the similar user with the similar product

5. Conclusion

Online marketing has been increasing year by year and brings many advantages together. Either suppliers or consumers get the benefit of online shopping in many ways. However, there are still some certain points to be developed for a better online shopping experience.

Figure 8.
Testing products
on users

Apparel online retailing is one of the product groups that increase market share year by year. Different from other online sales products, the usage rate of apparel is directly related to choosing the right size. When consumers are not happy with online purchased apparel size, they return the product that means extra cost and time for both parties in marketing. This is can be counted as one of the biggest barriers to expand online apparel sales.

In order to help for deciding right size in apparel online retailing, many different systems that work on different principle have been proposed. Some of these systems create 3D avatars from users' body measurement and try to show fitting of selected apparel on avatars. Furthermore, some systems use previously purchased apparel to guess the desired apparel size for users. However, there are not certain solutions to eliminate the fitting problem.

In this study, the method of fuzzy logic based apparel size finder was proposed. For this new method, any product with known measurements can be compared with users' body measurement based on the fuzzy logic rule and the best-fitted size can be selected for users. For this method, users create a profile with their body measurements. All body measurements must be gauged by users based on the provided guide to prevent possible faults that can be caused by measurement faults. In this case, male shirts were used and a guide explained how to measure body parts. The crucial point of this system is anyone who wears "small" size can also wear a bigger size than "small." For this problem, best-fitted size was decided based on the fitting index. Besides, a new method also proposed grouping users based on body measurements in order to find people with similar size. Users can upload a picture of online purchase apparels and other users can see how desired apparel fit on users with a similar body type.

In this example, where men's shirts are used, users can see whether there is a size issue for individual measurements and can decide the best for each body part. By this way, the user can evaluate the right size for even the best-fitted index. Furthermore, because of apparel size differences between companies, comparing body and apparel size will help to prevent faults against other systems, which use previously purchased apparel size. However, the success of this system is directly related with true body and apparel sizes and how to measure all parts must be explained clearly either for users or for companies.

It is believed that these new methods aid to a find an alternative way to solve one of the biggest problems in apparel online marketing.

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